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Robust feature extraction and salvage schemes for finger texture based biometrics

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Abstract: In this paper, an efficient human authentication method is proposed which utilizes Finger Texture (FT) patterns. This method consists of two essential contributions: a robust and automatic finger extraction method to isolate the fingers from the hand images; and a new feature extraction method based on an Enhanced Local Line Binary Pattern (ELLBP). To overcome poorly imaged regions of the FTs a method is suggested to salvage missing feature elements by exploiting the information embedded within the trained Probabilistic Neural Network (PNN) used to perform classification. Three databases have been applied in this paper: PolyU3D2D, IIT Delhi and spectral 460 from Multi-spectral CASIA images. Experimental studies show that the best result was achieved by using ELLBP feature extraction. Furthermore, the salvaging approach proved effective in increasing the verification rate.

1. Introduction

Finger Texture (FT) patterns are believed to be unique, even among the different fingers of the same person or between identical twins [1][2]. In addition, the FTs have protected patterns as they are located in the inner surface of the fist. Therefore, they offer a great degree of privacy as it is difficult to secure FTs without the person's knowledge.

Finger surfaces include features with noticeable characteristics with rich textures which will not change or be affected by emotional feelings, remain stable over age, are easy to access, require a low cost acquisition camera, can be acquired without contact and are resistant to tiredness [2]. In addition, it has been highlighted that FTs will not change over time, even for individuals who play racket-based sport such as tennis, despite such people physically using their inner fist muscles to grasp the racket [3]. Basically, the visible FTs consist of phalanxes and knuckles. The phalanxes include: a distal phalanx on the top of the finger including the nail, an intermediate phalanx located in the middle of the finger and a proximal phalanx on the base of the finger. The inner knuckles which create the principle lines in the finger are located as follows: the upper knuckle on the top of the finger, the middle knuckle in the middle of the finger and the lower knuckle at the base of the finger. Fig. 1a and Fig. 1b show the main parts of the hand and FTs respectively.

The aim of this paper is to present an efficient human authentication method based on the FT biometric patterns. There are several important areas where this study makes original contributions:

- A robust method for finger extractions is described, where each finger is considered as an object. Also, the acquired Region Of Interest (ROI) is adaptive to each finger size and more features are thereby collected from each finger.
- An enhanced method for the Local Line Binary Pattern (LLBP) is proposed called Enhanced LLBP (ELLBP).
- Verification performance is evaluated for limited views or even missing fingers, and a suggested approach is described to enhance the verification rates in these cases by salvaging features embedded in the trained PNN.

After the introduction, this paper is organized as follows: Section II gives a brief summary of prior work. Section III explains the main block diagram of our proposed scheme. Section IV describes the proposed method for finger extractions. Section V details the feature extraction, and Section VI the PNN together with the approach to salvage missing features. Section VII discusses our results and findings. Section VIII concludes this paper.

2. Related work

Several studies have utilized the inner finger surface characteristics. For example, eigenfinger with eigenpalm were applied in a biometric identification system [3] as perhaps the first work which utilized FTs in terms of human recognition. Ferrer *et al.* [4] proposed a combination of FT print, palm and hand geometry to realize a low cost multi-modal identification system. Three types of fusion were examined in this work: feature fusion, score-level fusion and decision fusion. They concluded that the decision fusion attained the best results. Pavesic *et al.* [5] produced a comparison study for fingerprint and FT surface based on principal component analysis, the most discriminant features and regularized-direct linear discriminant analysis. The best results were reported for the regularized-direct linear discriminant analysis method. Michael *et al.* [6] illustrated a robust recognition system by combining the knuckle print and the palm print in the case of verification. The feature extraction method which was used was the Ridgelet Transform (RT) for the FTs and the wavelet Gabor competitive code for the palm print. No standard resizing was used for the FT regions. Kanhangad *et al.* [7] used the FTs as a part of a fusion study between hand geometry, palm print and finger surfaces to enhance contactless hand verification. A low resolution contactless database was established in this work. Furthermore, an interesting idea to extract the ROI region from the finger image was proposed, where the largest adaptive rectangle method was applied. However, the lower knuckles of the fingers were not included in their ROIs.

Kumar and Zhou [8] investigated very low resolution finger images (~ 50 dpi), and obtained promising results in terms of identification. Only a small part of the index finger image was employed, so, it can be argued that this is not enough to achieve best performance or represent a comprehensive study. Kumar and Zhou [9] examined vein and texture images for just two fingers (index and/or middle) in two experiments, where different numbers of subjects were employed for the personal identification. The main problem was that the FT database was for just part of the inner surface of the finger and may not be sufficient for a satisfactory identification rate. Therefore, the authors used a fusion method mainly based on the vein patterns. Liu *et al.* [10] suggested an Improved Local Binary Pattern Neighbours (ILBPN) method to analyse the inner knuckle print.

It consists of image preprocessing followed by an improved Local Binary Pattern (LBP) operator. Then, the uniform LBP values have been calculated for each pixel and binary images have been generated for each LBP uniform value. Liu *et al.* [11] also presented a new approach to use part of the inner knuckles (middle knuckles from the ring and middle fingers), and a database was established from contactless fingers restricted by a back-plate and a peg. The Gabor filter and derived line detection methods were used as feature extractions for the inner knuckles. The major problem was that just a small part of the FT was used for the recognition. Bhaskar and Veluchamy [2] have explained that using a combination between the palm print and the inner finger surfaces can obtain higher recognition rates than the combination between the palm print and the outer finger knuckles. Feature level fusion method has been employed for the combination and a support vector machine has been applied for the classification.

As it can be seen from the above literature several recent studies have been undertaken for the FT as part of biometric recognition. It can also be observed that some publications work with limited parts of the finger surface.

In view of this we believe it is worth intensively investigating FT patterns and fully employing their characteristics in human verification.

Fig. 1: *FT parts and the main block diagram scheme:*

a The main parts of the hand

b The finger texture parts in a single finger

c The main block diagram of the proposed scheme, showing both training and testing pathways

3. Proposed Methodology

As mentioned previously, the contribution of this paper has different parts. First of all, establishing robust processing to extract the five fingers. To achieve this, multiple image processing steps are adopted, where the five finger images are extracted from a large number of images from a contact free hand database. This is followed by segmenting each finger image to define a ROI, from which full FT features are collected. After that, the new approach for feature extraction named ELLBP is employed and will be compared with other LBP techniques. The next step is preparing the input to the neural network. Instead of using the histogram features a simple and efficient statistical calculation is described to collect the variances of the extracted features. This method involves blocking each ROI into matrices, calculating the Coefficient of Variance (COV) of each matrix and arranging the values to construct the acquired vector. Then, a PNN is used to verify the authentication performance. Moreover, we have increased our experiments to examine the verification rate with missing finger elements. For example, removing the distal phalanx, or the distal and the intermediate phalanxes or even a full finger image. A proposed approach is also suggested and implemented to increase the verification performance rates in the case of such missing elements. Fig. 1c shows the general block diagram of our proposed scheme.

4. Robust finger extraction method

The extraction of the FT pattern from a hand image is not a straightforward procedure. Therefore, different image processing operations are employed to extract the five fingers from a hand image. The image preprocessing steps begin by reading the colour image and then converting it to an 8-bit grayscale image denoted as $I(x, y) : Z^2[0, 255]$. The converted grayscale hand image is given in Fig. 2a. Hence, it is translated to a binary image by using a threshold τ . It has been observed that the value of τ should be adaptive in order to maintain the hand image and it could be controlled by the number of fingers or objects that are obtained.

There will still be, however, some binary noise outside the hand region as shown in Fig. 2b, the following steps can be used to remove them [12]: specifying the white areas; calculating the size of each area; and deleting all small areas and preserving the largest white area. The resulting image is then denoted as $B(x, y)$, see Fig. 2c, and the complement will be defined as $\bar{B}(x, y) : Z^2\{1, 0\}$. Nevertheless, there may still be some unexpected noise connected to the hand image as shown in Fig. 2d. To overcome this problem, a ‘major’ morphological filter can be executed to dilate these artifacts. The filter mask size is 3×3 pixels. This is performed by converting the black pixels with the majority white neighbourhood to logical one [13]. The reason for not using other types of morphological operations is to avoid erosions or degradation in the fingers borders. So, empirically, it has been found that this ‘major’ filter obtained the most satisfactory implementation.

In the case of specifying the main point of the thumb, another scanning operation is performed for the complement image $\bar{B}(x, y)$ until two areas are detected: a small area, which represents the thumb, and a large area for the rest of the fingers with a part of the hand as shown in Fig. 3a. The tip point of each finger could be determined as the furthest top left side points from the object. Whereas, the valley points can be specified simply by assigning the separating points between the two objects.

Another scan can then be executed to verify the four finger objects (index, middle, ring and little), where each object could be assigned by one colour. So, the four finger objects could be represented by four different colours with a black background. After that, the tip points will be assigned

Fig. 2: *Image preprocessing operations:*
a Original hand image
b Binary image
c Binary image after deleting the small regions
d Image complement

Fig. 3: *Five finger extractions:*
a Thumb object with the tip and valley points
b Four finger objects with the tips points
c Background objects with the valley points
d Original hand image with the tips and valleys points

where each point could be defined as the furthest left point in the object, see Fig. 3b. Similarly, the background is converted into colour objects to specify easily the valley points. Each tip point is extended to be a border between the two objects as given in Fig. 3c. From this point the valleys have been assigned between the fingers, where each valley point can be denoted as the furthest right point in the object. A hand image with all tips and valley points is given in Fig. 3d.

Symmetric points can also be calculated to describe the following locations: before the thumb, before the index finger and after the little finger. These points can be derived from the tip and valley locations, where the distance between the tip and valley points is equal to the distance between the tip and the symmetric point, this method is explained in [3] and [5]. Henceforth, the original hand image will be combined with the pure black background as this is more robust than using the original background. See equation (1):

$$I_{new}(x, y) = I(x, y) \times B(x, y) \quad (1)$$

Then, this image needs to be rotated. The best rotation angle to be established is between the tip and the middle of the finger base points, which is defined as the point between the two valleys or between a valley and a symmetric point. To acquire the rotation angle, equation (2) [14] is employed in our work:

Fig. 4: Example of five finger images, their ROIs and the ELLBPs: the first column in the left represents the original finger images, the middle column represents the ROI of each finger and the last column represents the ELLBP image for each finger. While the first row is for the thumb, the second row is for the index finger, the third row is for the middle finger, the fourth row is for the ring finger and the fifth row is for the little finger

$$angle = \tan^{-1} \left(\frac{|T(y) - B(y)|}{|T(x) - B(x)|} \right) \times \frac{180}{\pi} \quad (2)$$

where: $T(x)$ and $T(y)$ are the x and y components respectively of the tip point of any finger, $B(x)$ and $B(y)$ are the x and y components respectively of the middle point in the base of the finger between the two valleys or between a valley and a symmetric point, and $angle$ is the rotation angle.

Equation (2) will be used for each finger in order to determine its direction to be extracted in a separate image. It is worth mentioning that our finger extraction strategy has fewer points and less complexity compared to [7], where 4 points have been used in our work including the essential points to detect the finger orientation compared with 6 extra points established in [7]. The proposed finger extraction is inevitable for contactless hand images, where it can deal efficiently with the

translation of the hand images. In addition, it maintains the finger images rather than the hand image.

Consequently, the ROIs have been determined according to [7], where each finger was adaptively eliminated under largest inner rectangle. It has been noticed that this method is more efficient than in [5] and [3] as they considered that the ROIs have specific ratios between the width and length of the fingers. We believe that there is no universal fixed proportional ratio between a finger's length and width. Furthermore, the lower knuckles have been included in our proposed ROIs.

After specifying the ROIs, a fixed resize has been applied to each finger image in order to normalize them into fixed sized vectors. In this paper, the normalization resize is considered equal to 30×150 after any LBP operator type.

5. FEATURE EXTRACTION

It has been cited that one of the best feature extraction methods which is illumination invariant is the LBP method. It has been used in various fields such as face recognition [15], face expression recognition [16] and object detection [17]. Different enhancements have been given for this effective method. In the following sections the basic LBP method will be explained, and then, some modified LBP methods will be described. After that, our proposed method will be given:

5.1. LBP

The LBP method was invented by Ojala *et al.* [18] as a promising method for texture analysis. The main idea of this method is that each non-overlapped 3×3 neighbourhood pixels of an image is thresholded by the pixel in the centre. This will produce a binary expression in each neighbourhood pixel. This binary code is converted to a decimal value, which will represent the new centre value and it will be within the range of $[0, 255]$ [18]. The basic equation which defines the LBP is:

$$LBP = \sum_{p=0}^7 s(g_p - g_c)2^p, \quad s(x) = \begin{cases} 1 & , \quad x \geq 0 \\ 0 & , \quad x < 0 \end{cases} \quad (3)$$

where: g_c , g_p and s are the center pixel of the gray-level image patch, circular neighbourhood pixels and the basic LBP transformation, respectively.

5.2. Enhanced LBP

To enhance the LBP feature, ILBPN has been suggested for the inner finger knuckles in [10]. The operator of ILBPN has been described as a horizontal window of 9 pixels. The pixel value in the middle will be recalculated according to the demonstrated example shown in Fig. 5a.

This ILBPN method is more likely to be used for the patterns in a vertical direction as illustrated in [10]. Whilst, a LLBP which is suggested in [19] is more efficient. This operator considers the patterns in both horizontal and vertical directions, see Fig. 5b. The LLBP values can be calculated according to the following equations [19]:

$$LLBP_h(N, c) = \sum_{n=1}^{c-1} s(h_n - h_c)2^{(c-n-1)} + \sum_{n=c+1}^N s(h_n - h_c)2^{(n-c-1)} \quad (4)$$

a

b

Fig. 5: Examples of ILBPN and LLBP operators:

a An example of the ILBPN operator which has been suggested in [10]

b An example of the LLBP operator which has been suggested in [19]

$$LLBP_v(N, c) = \sum_{n=1}^{c-1} s(v_n - v_c)2^{(c-n-1)} + \sum_{n=c+1}^N s(v_n - v_c)2^{(n-c-1)} \quad (5)$$

$$LLBP_m = \sqrt{LLBP_h^2 + LLBP_v^2} \quad (6)$$

where: $LLBP_h$ represents the horizontal direction value, $LLBP_v$ represents the vertical direction value, $LLBP_m$ represents the magnitude value between the horizontal and vertical directions, N is the line length in pixels, c is the position of the centre pixel $= \lceil \frac{N}{2} \rceil$ where $\lceil \cdot \rceil$ is the ceiling operator, h_c represents the centre of the horizontal line, v_c represents the centre of the vertical line, h_n represents the pixels along the horizontal line, v_n represents the pixels along the vertical line and s represents the same function as in the LBP.

Moreover, Petpon and Srisuk [19] illustrated that the best results can be obtained for the line lengths of $N = 13, 15, 17$ or 19 ; because they roughly cover the possible patterns to the maximum grayscale value (255).

We next suggest an enhanced method called the Enhanced Local Line Binary Pattern (ELLBP). This method will be illustrated in the next section.

5.3. ELLBP

Due to the fact that the texture of the inner finger surfaces mainly consist of vertical and horizontal patterns. We suggest the ELLBP operator as an efficient method to describe these textures.

The main problem in the LLBP can be found in its amplitude equation (6), which is not appropriate to provide directional information as in a phase/gradient calculation. It can be influenced by noise, brightness and range value [20], therefore, it cannot give full description of image textures. On the other hand, fusing the vertical and horizontal vectors according to the weighted summation rule is useful to describe the finger textures. Thus, equation (7) is suggested to be used instead of equation (6):

$$ELLBP_m = ((v_1 \times LLBP_h) + (v_2 \times LLBP_v))/2 \quad (7)$$

where v_1 and v_2 are the directional strengths ($v_1 + v_2 = 1$); these two parameters can be used to control the density of the two directions. The reason of dividing by 2 is to get the average value between the weighted summation of the values calculated from the vertical and horizontal lines.

Hence, we have employed three databases and each one of them consists of different characteristics, so, it is not easy to establish v_1 and v_2 values. For instance, multi-spectral CASIA is a low resolution database acquired from spectral sensors, while the PolyU3D2D is a very low resolution database acquired for hands located at a long distance from the capturing device. Therefore, many experiments were performed to establish a relationship between the two parameters. Then, it has been found that for choosing the values of v_1 and v_2 the following useful idea can be utilized: dividing the training patterns into training and validation parts. Then, the weighted summation will be examined in the training phase according to the partitioned parts. After that, the best values can be used during the testing phase. This idea has been inspired from [21], where three novelties to acquire the weighted summation values have been introduced. All of these methods were based on using only the training data. However, massive calculations have been applied in [21] to collect the precise values of the weights in each of the three suggested methods.

In our approach, a fixed feature vector length size N is used equal to 17 pixels to cover the possible textures in the grayscale image.

5.4. Feature vector preparation

To form the feature vector, usually histogram features are applied after the LBP image operator. However, some important spatial information may not be well described as illustrated in [10]. Thus, statistical calculations have been employed to describe the variances of the FT characteristics of the operator image.

Each input image is partitioned into non-overlapped blocks with a fixed size of 5×5 following [22]. The COV value is calculated for each block as stored in equation (8) [23]:

$$COV_{seg} = \frac{STD_{seg}}{M_{seg}} \quad (8)$$

where: seg , M , STD and COV are respectively the matrix of 5×5 pixels, the average, the standard deviation and the coefficient of variance. The COV value has the following advantages: it reduces the image size, where each image block has been reduced to one value; is easy to calculate; fast to execute; and it efficiently describes the variances between the pixel values.

All COV values have been arranged into a 1-D vector. This vector is then applied as the input to the PNN to classify the variances between the data.

6. PNN and missing features

6.1. PNN

In our work, a supervised PNN is investigated and adapted to achieve its tasks. The main structure of the PNN is that it consists of multi-layers: the input layer, the hidden layer, the summation layer and the decision layer. Fig. 6 shows the general form of the PNN.

Within the first hidden layer of the PNN, the node outputs are calculated as [24][25]:

$$Z_{i,j} = \exp \left[-\frac{(\mathbf{x} - \mathbf{w}_{i,j})^T (\mathbf{x} - \mathbf{w}_{i,j})}{2\sigma^2} \right] , \quad i = 1, 2, \dots, p \quad , \quad j = 1, 2, \dots, c \quad (9)$$

where: $Z_{i,j}$ is the probability output value of a hidden node, $\mathbf{x}$ the input vector $\mathbf{x} = [x_1, x_2, \dots, x_n]^T$, $\mathbf{w}_{i,j}$ is the i th element from class j , that is, the training vector $\mathbf{w}_{i,j} = [w_1, w_2, \dots, w_n]^T$, p represents the number of input training patterns for each class and c is the number of classes.

In other words, the PNN will store the weight values equal to the input training vectors during the training phase.

Next, with the PNN the probabilistic values for the same input vector will be calculated by the summation layer to each node (or each class) according to the following equation:

$$S_j = \frac{1}{p} \sum_{i=1}^p Z_{i,j} \quad , \quad j = 1, 2, \dots, c \quad (10)$$

where: S_j is the output of the summation layer and p is the number of training patterns.

From this point the decision layer will establish the maximum S_j value and provide logic one in

Fig. 6: The general form of the PNN with its layers

the decision class D_j for the given input vector while all other classes will be set to zero.

There are some important advantages of using the PNN [26]: it has a very short training time; it does not require more than one iteration; it does not struggle from the local minimum error as in the backpropagation network; it has a flexible structure, where it is easy to add or remove training data; and one of the most interesting advantages is that the input training patterns will be saved within the hidden layer.

6.2. Missing FT features

Missing finger elements have also been investigated in this work, where this can be considered as a new investigation in the case of Finger Texture (FT) patterns. No publication has explored this to the best of our knowledge. The missing elements have been considered as zero inputs to the neural network [24]. Empirically, the first quarter of the ROI represents missing the distal phalanx and the first half ROI represents missing the distal and the intermediate phalanxes in the four fingers (index, middle, ring and little). Whereas, the first third part of the ROI represents the missing distal phalanx for the thumb. The verification performance will be expected to be reduced after removing some parts of the inputs. Therefore, an approach is suggested to salvage the missing elements by taking advantage from the distance equation (11) in the probability equation (9):

$$dist = [(\mathbf{x} - \mathbf{w}_{i,j})^T(\mathbf{x} - \mathbf{w}_{i,j})] \quad , \quad i = 1, 2, \dots, p \quad , \quad j = 1, 2, \dots, c \quad (11)$$

Briefly, each node in the hidden layer in the PNN already saves the full training pattern during the training phase as described in [26]. To describe the salvage approach, the following justification can be described:

Assume: $x'_q = x_k$ when $x_k \neq 0$ ($k = 1, 2, \dots, n$).

Similarly, $w'_{u,v} = w_{i,j}$ when $w_{i,j}$ corresponds to the x'_q ($i = 1, 2, \dots, p$) ($j = 1, 2, \dots, c$).

Also, $dist'$ represents the distance equation (11) excluding the missing values. It can be represented as shown in the equation (12):

$$dist' = [(\mathbf{x}' - \mathbf{w}'_{u,v})^T(\mathbf{x}' - \mathbf{w}'_{u,v})] \quad , \quad u = 1, 2, \dots, p \quad , \quad v = 1, 2, \dots, c \quad (12)$$

Under the assumptions of clear quality images: the salvaging approach assumes that the stored weight pattern, which can be identified among the different classes according to the minimum $dist'$ value and will generally salvage or rescue the missing data. In other words, $x_k = w_{i,j}$ such that the $dist'$ value is the minimum and $x_k = 0$ for $k = 1, 2, \dots, n$.

From this point, one of the three possibilities can be achieved:

1. The closest pattern of the same class may be confirmed. In this case the missing elements will be salvaged to the same person.
2. The closest pattern may be from a different class, but the probability functions and summations in equations (9) and (10) respectively will not define the false class. In this case the salvaged missing elements will be from a different person or class. However, the probability functions of the other weighted patterns from the same class will dominate the wrong decision and it will not be indicated. Instead, the right authentication will still attain.
3. The closest pattern from a different class may be confirmed and the probability functions in equations (9) and (10) will verify the false class. In this case the wrong verification decision can be achieved, but this is very unlikely due to the assumption above.

This method has effective performance and will be verified in the next section. It is noteworthy that this salvaging approach could be exploited in many biometric applications, where good quality images are observed.

7. RESULTS AND DISCUSSIONS

In this work, three databases have been employed: PolyU3D2D from the Hong Kong Polytechnic University Contact free 2D Hand Images Database (Version 1.0) [27], IIT Delhi Palmprint Image Database (version 1.0) [28] [29] and spectral number 460 from the multi-spectral CASIA palmprint image database (version 1.0) [30]. A total of 8850 finger images acquired from 1770 hand images have been employed for the PolyU3D2D, where each person has contributed 10 images. For the IIT Delhi Database, 4440 finger images have been utilized from 888 hand images. Each person has participated with 6 images. Furthermore, 3000 finger images extracted from 600 hand images within the spectral 460 part of the CASIA database have been used. Also, each person has contributed 6 images. The reason of using the spectral number 460 is because it consists of the

Table 1 Summary of related work for extracting the ROIs from the four finger images

Comparison part	Suggested Process	Ribaric and Fratric [3]	Pavesic <i>et al.</i> [5]	Kanhangad <i>et al.</i> [7]
Binarization threshold	Adaptive value	Fixed value	Fixed value	Using Otsu [32]
Upper knuckle	Include	Include	Partially include	Include
Lower knuckle	Include	Partially include	Partially include	Not include
Full finger width	Include	Not always include	Partially include	Include
ROI rectangle	Adaptive rectangle	Proportional rectangle	Proportional rectangle	Adaptive rectangle
Assigned points	4	10	10	9
No. of fingers	5	5	4	4

Table 2 The EER results for parts of four fingers, full textures of four fingers and full textures of five fingers

Method	Database	EER (part textures of 4 fingers)	EER (full textures of 4 fingers)	EER (full textures of 5 fingers)
CompCode [7]	PolyU3D2D	6%	—	—
IFE [22]	PolyU3D2D	5.42%	4.07%	—
	PolyU3D2D	0.68%	0.45%	0.34%
Suggested	IIT Delhi	—	3.38%	1.35%
ELLBP	CASIA (spectral 460)	—	5%	3%

texture patterns according to [31].

The following process has been implemented on all the 2D right hand images in all three databases: five samples for each person have been used in the training phase following [7]; the remaining samples have been used in the testing stage; five finger images are extracted in our work; and each set of finger vectors has been concatenated serially to generate one input vector for each individual as in [7].

First of all, the suggested finger extraction method has been successfully implemented and it is found to be robust in collecting many FT features. Three methods were compared with ours as demonstrated in Table 1. In [3] and [5] a fixed threshold was used for the image binarization; then the database could be considered as high resolution data because it would be acquired from a touch scanner. Although Otsu's threshold was used for the image binarization in [7], after utilizing this in our work it has been noticed that applying an adaptive threshold is better to maintain the 2D hand images. That explains why the opening morphological operations was used in [7] after the binarization process. While, these operations are not required after using the adaptive threshold. On the other hand, in all three publications [3] [5] and [7] full ROI regions are not employed and that caused some important FT characteristics to be lost. In addition, in [5] and [7] the thumb is neglected which could cause an important enhancement to their approaches.

Moreover, decreasing the number of assigned points in each finger would reduce the computational complexity of the finger extraction model. In contrast, assigning more points is more likely to be used in the high resolution images as in [3] and [5]. Also, using the adaptive largest rectangle area in each finger is already covering the features in the wide finger area [7], so, it seems that there is no need to increase the complexity in determining many points.

As mentioned, in our proposed method more features are included in the ROI of each finger and this has decreased the error rate of the FT biometric authentication as given in Table 2, where a comparison according to the state-of-the-art is given.

Table 3 Comparisons between different LBP types for the five fingers with the full texture regions

PolyU3D2D database			
Reference	Method	Parameters	EER
Wolf <i>et al.</i> [33]	FPLBP	$w=3, r1=4, r2=5, S=8, \alpha=1$ and $\tau=0.01$	9.38%
	TPLBP	$w=3, r=2, S=8, \alpha=5$ and $\tau=0.01$	1.47%
Jin <i>et al.</i> [34]	ILBP	$P=8$	0.79%
Tao and Veldhuis [35]	SLBP	$P=8$	1.47%
Petpon and Srisuk [19]	LLBP	$N=19$	1.24%
	LLBP	$N=17$	0.68%
	LLBP	$N=15$	0.79%
	LLBP	$N=13$	0.68%
Liu <i>et al.</i> [10]	ILBPN	—	10.17%
Our approach	ELLBP	—	0.34%
IIT Delhi database			
Reference	Method	Parameters	EER
Wolf <i>et al.</i> [33]	FPLBP	$w=3, r1=4, r2=5, S=8, \alpha=1$ and $\tau=0.01$	15.54%
	TPLBP	$w=3, r=2, S=8, \alpha=5$ and $\tau=0.01$	6.76%
Jin <i>et al.</i> [34]	ILBP	$P=8$	2.70%
Tao and Veldhuis [35]	SLBP	$P=8$	2.70%
Petpon and Srisuk [19]	LLBP	$N=19$	4.05%
	LLBP	$N=17$	2.70%
	LLBP	$N=15$	2.70%
	LLBP	$N=13$	2.03%
Liu <i>et al.</i> [10]	ILBPN	—	29.05%
Our approach	ELLBP	—	1.35%
CASIA database (spectral no. 460)			
Reference	Method	Parameters	EER
Wolf <i>et al.</i> [33]	FPLBP	$w=3, r1=4, r2=5, S=8, \alpha=1$ and $\tau=0.01$	45%
	TPLBP	$w=3, r=2, S=8, \alpha=5$ and $\tau=0.01$	31%
Jin <i>et al.</i> [34]	ILBP	$P=8$	9%
Tao and Veldhuis [35]	SLBP	$P=8$	31%
Petpon and Srisuk [19]	LLBP	$N=19$	5%
	LLBP	$N=17$	8%
	LLBP	$N=15$	6%
	LLBP	$N=13$	6%
Liu <i>et al.</i> [10]	ILBPN	—	58%
Our approach	ELLBP	—	3%

Table 4 The timing comparison between the different LBP operators for a single finger

Reference	Method	Parameters	Time (sec.)
Wolf <i>et al.</i> [33]	FPLBP	$w=3, r1=4, r2=5, S=8, \alpha=1$ and $\tau=0.01$	0.007
	TPLBP	$w=3, r=2, S=8, \alpha=5$ and $\tau=0.01$	0.007
Jin <i>et al.</i> [34]	ILBP	$P=8$	0.08
Tao and Veldhuis [35]	SLBP	$P=8$	0.03
Petpon and Srisuk [19]	LLBP	$N=19$	0.078
	LLBP	$N=17$	0.07
	LLBP	$N=15$	0.063
	LLBP	$N=13$	0.06
Liu <i>et al.</i> [10]	ILBPN	—	0.034
Our approach	ELLBP	—	0.06

Table 5 The EERs before and after the suggested salvaging method for the ELLBP

PolyU3D2D database		
The missing element	EER	EER after the salvaging missing elements
Distal phalanx from the index finger	0.45%	0.34%
Distal phalanx from the middle finger	0.45%	0.23%
Distal phalanx from the ring finger	0.45%	0.34%
Distal phalanx from the little finger	0.68%	0.34%
Distal phalanx from the thumb	0.79%	0.45%
Distal and intermediate phalanxes from the index finger	0.68%	0.45%
Distal and intermediate phalanxes from the middle finger	0.68%	0.34%
Distal and intermediate phalanxes from the ring finger	1.24%	0.45%
Distal and intermediate phalanxes from the little finger	1.24%	0.34%
Index finger	3.16%	0.68%
Middle finger	3.62%	0.45%
Ring finger	3.28%	0.45%
Little finger	2.82%	0.45%
thumb	2.49%	0.57%
Index finger + Middle finger	49.38%	0.90%
Middle finger + Ring finger	54.92%	1.24%
Ring finger + Little finger	42.71%	0.45%
IIT Delhi database		
The missing element	EER	EER after the salvaging missing elements
Distal phalanx from the index finger	2.70%	1.35%
Distal phalanx from the middle finger	3.38%	1.35%
Distal phalanx from the ring finger	2.70%	2.03%
Distal phalanx from the little finger	1.35%	1.35%
Distal phalanx from the thumb	2.03%	2.03%
Distal and intermediate phalanxes from the index finger	4.73%	1.35%
Distal and intermediate phalanxes from the middle finger	2.03%	2.03%
Distal and intermediate phalanxes from the ring finger	3.38%	2.70%
Distal and intermediate phalanxes from the little finger	3.38%	1.35%
Index finger	8.78%	1.35%
Middle finger	8.78%	1.35%
Ring finger	8.78%	2.70%
Little finger	10.14%	2.03%
thumb	4.05%	3.38%
Index finger + Middle finger	52.03%	3.38%
Middle finger + Ring finger	49.32%	4.73%
Ring finger + Little finger	54.05%	4.73%
CASIA database (spectral no. 460)		
The missing element	EER	EER after the salvaging missing elements
Distal phalanx from the index finger	6%	3%
Distal phalanx from the middle finger	5%	4%
Distal phalanx from the ring finger	4%	3%
Distal phalanx from the little finger	4%	4%
Distal phalanx from the thumb	8%	5%
Distal and intermediate phalanxes from the index finger	8%	4%
Distal and intermediate phalanxes from the middle finger	5%	4%
Distal and intermediate phalanxes from the ring finger	6%	1%
Distal and intermediate phalanxes from the little finger	5%	3%
Index finger	16%	7%
Middle finger	14%	6%
Ring finger	11%	3%
Little finger	9%	4%
thumb	23%	5%
Index finger + Middle finger	62%	10%
Middle finger + Ring finger	43%	6%
Ring finger + Little finger	35%	6%

From Table 2 it is clear that using more features will improve performance in terms of the EER. This issue has been recorded in [22] for the main four fingers and by using a new feature extraction method has been applied named Image Feature Enhancement (IFE). So, the FT rates after adding the third knuckle are better than the FT rates without this important feature. Similarly, adding the FTs of the thumb will further enhance the verification rate compared with using just four fingers. In Table 3 different LBP methods are simulated and implemented as feature textures to examine the best feature description method. It shows that utilizing the ILBPN produces inferior results, over all the three databases. The reason is that it is designed only for the vertical inner knuckles. Alternatively, our proposed ELLBP method has generated the best EERs for all three databases. It can be seen from Table 4 that our proposed ELLBP required shorter time than the LLBP (N=17) which can be considered as the closest method to the ELLBP approach. Furthermore, the LLBP obtained the nearest recognition results, which are still far from those achieved with our proposed ELLBP method, which attained the best performance. The computational time has been recorded with the following specifications: (3.2 GHz Intel Core i5 processor with 8 GB of RAM). In order to evaluate our suggested method in terms of missing elements, the three databases have been applied for the comparison and examination purposes as given in Table 5. Different experiments have been applied: missing the distal phalanx from each finger, missing the distal and the intermediate phalanxes from each finger except the thumb and missing the whole finger. It is clear from the Table 5 that missing distal phalanx will affect slightly the verification rate and missing the distal and intermediate phalanxes will affect significantly the results. On the other hand, missing a one or two complete fingers can lead to the wrong verification decision. Moreover, the proposed salvaging method proved its ability to enhance the verification performance, where significant improvements can be seen in the table for the three employed databases. These improvements are increased with more missing FT elements. Some missing elements in Table 5 have not been affected by the suggested salvaging method such as missing the distal phalanx from the little finger in the IIT Delhi database, because these regions might not actually change the verification rate. Furthermore, using the proposed salvage method may affect the authentication performance to be slightly better than the reported verification rate before the missing textures.

8. CONCLUSION

The FT biometric has been investigated intensively in this paper. Contactless hand images were used in this work collected from three different databases: PolyU3D2D, IIT Delhi and CASIA (spectral 460). A robust approach has been introduced to extract the five finger images based on an object detection method; then a fixed ROI procedure was applied to all finger surfaces, where the largest inner rectangle has been considered adaptively to collect as many features as possible. Moreover, we suggested an enhanced feature extraction method named ELLBP based on the fusion between the vertical and horizontal FT patterns. This enhanced method has been compared with different LBP types and it obtained the best results. Finally, a proposed approach has been suggested to solve the problems of missing elements in the FT. As a result of this research, it can be noted that the ELLBP method for feature extraction reported the highest verification rate. In addition, the proposed salvaging of missing feature elements was confirmed to successively enhance the authentication performance rate.

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- “IIT Delhi Palmprint Image Database version 1.0”.
- “Portions of the research in this paper use the CASIA-MS-PalmprintV1 collected by the Chinese Academy of Sciences’ Institute of Automation (CASIA) ”.

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